Ares I-X Ground Diagnostic Prototype

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Introduction

- Automated pre-launch diagnostics for launch vehicles offers the following potential benefits:
  - Improved safety
  - Reduced cost
  - Reduced launch delays
- Can include data from vehicle assembly, and from assembled vehicle while it is on the launch pad (from pre-launch umbilical)

What is Ares I-X?

Ares I-X was the first test flight of Ares I. It had a dummy second stage and a dummy capsule, and launched on 10/28/2009.

Definitions

- **Anomaly detection:** detecting that something is unusual
- **Failure**: The unacceptable performance of intended **function**.
- **Failure Detection:** Deciding that a **failure** exists.
- **Fault Diagnosis**: Determining the possible causes of a **failure**.
- **Fault Isolation**: Determining the possible locations of a hypothesized **failure** cause, within a defined level of granularity.
- All are part of Integrated Systems Health Management (ISHM)
- All take as input sensor values and command stream.

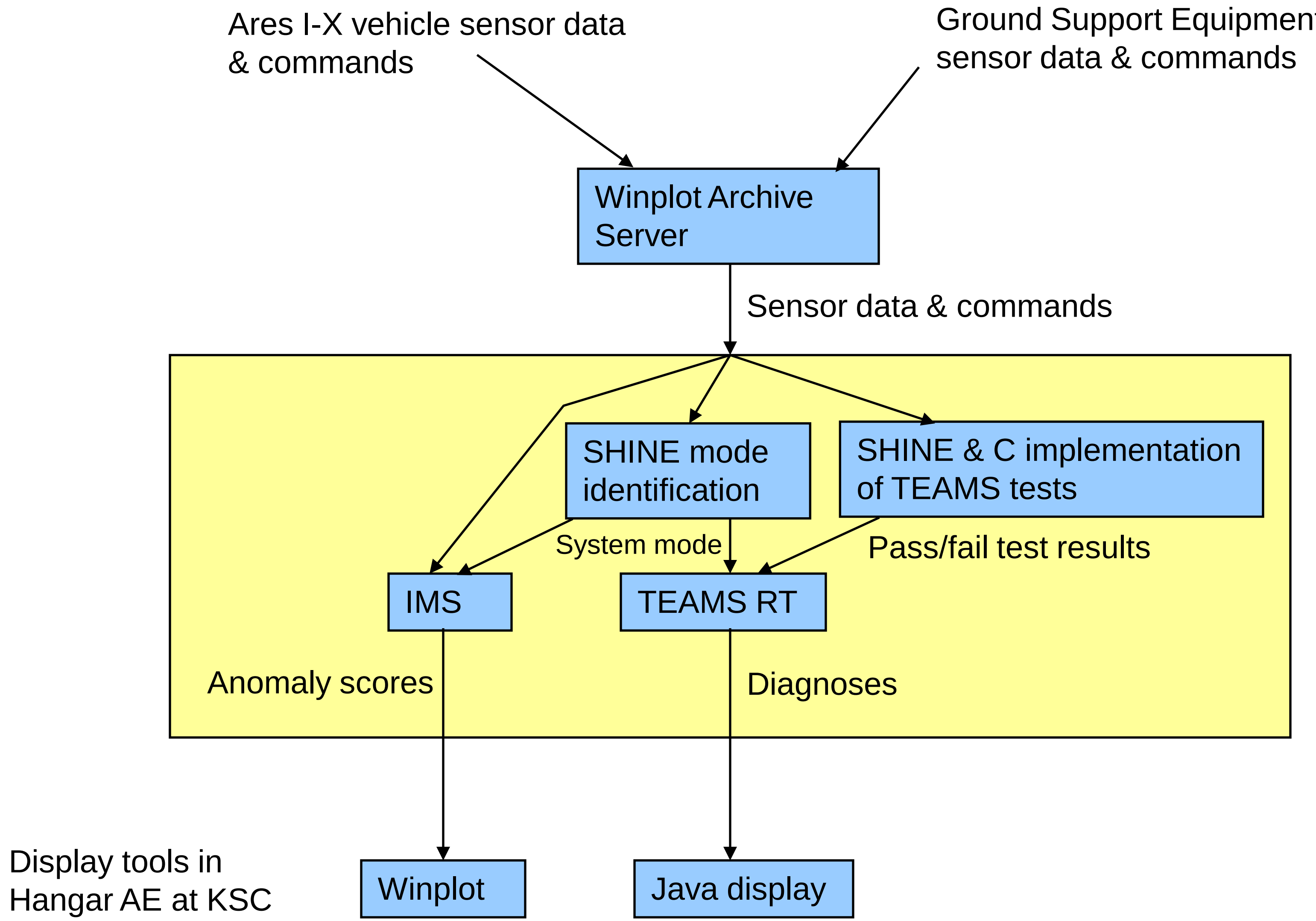
Scope of Ares I-X Ground Diagnostic Prototype

- Anomaly detection, failure detection, fault isolation, and fault diagnosis for Ares I-X while it is in the Vehicle Assembly Building and while it is on the launch pad
- Focused on the first-stage thrust vector control (TVC) and the associated ground hydraulics
- Deployed diagnostic software to Hangar AE at NASA KSC
- Used near-real-time data from the VAB and the pad
- Integrated the diagnostic software with existing software at NASA KSC
- Assessed the difficulty of certifying the software for human spaceflight
- Intended to serve as a prototype of the ground diagnostic system for Ares I

Tools used in GDP

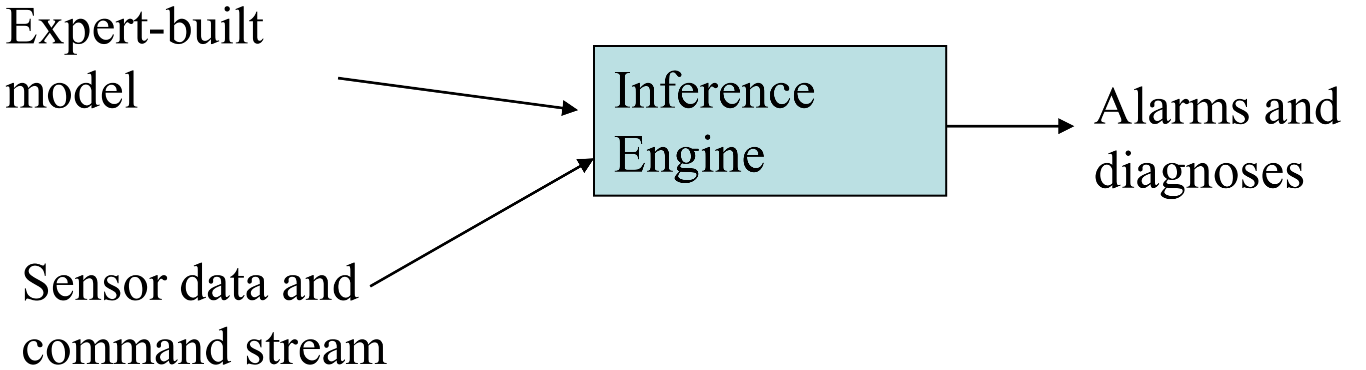
- TEAMS-RT, a model-based tool for fault isolation and diagnosis
- IMS, a data-driven tool for anomaly detection
- SHINE, a rule-based tool that we are using for failure detection

Simplified GDP Architecture



Model-based Diagnostics

- Human experts build a hierarchical model of the system.
- The model describes how the components of the system should work, their interconnections, and their failure modes.
- The component models can be physics-based or finite state machines.
- An inference engine uses the model and the real-time data and command stream to determine the state of the system and to diagnose failures, including reasoning about multi-component failures.
- Ames' Livingstone and HyDE, JPL's MEXEC, and TEAMS RT (commercial product) use this approach.

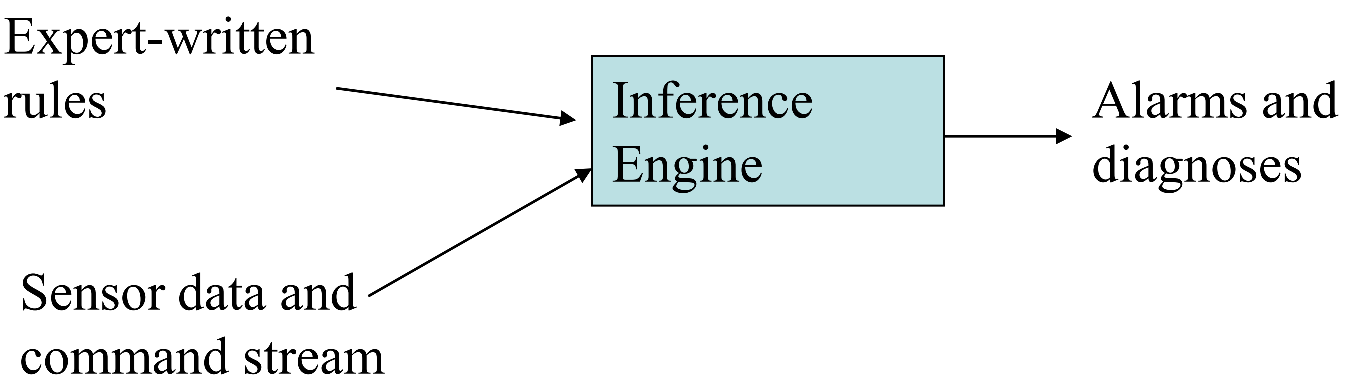


TEAMS RT

- Model-based tool for fault isolation and diagnosis
- Commercial product from QSI; developed using NASA ARC SBIR funding
- Uses a qualitative model of failure propagation
- Is being used by Honeywell to model the Orion CEV under subcontract to Lockheed Martin (will be certified and flown)
- Requires “wrapper” code to convert sensor values into “pass/fail” test results and to identify the system mode.

Rule-based expert systems

- Human experts write rules in a special-purpose language.
- The rules map fault signatures to faults.
- An inference engine decides which rules are applicable and executes them.
- JPL's SHINE uses this approach (TRL 9 heritage)
- G2 (commercial product) also uses this approach.

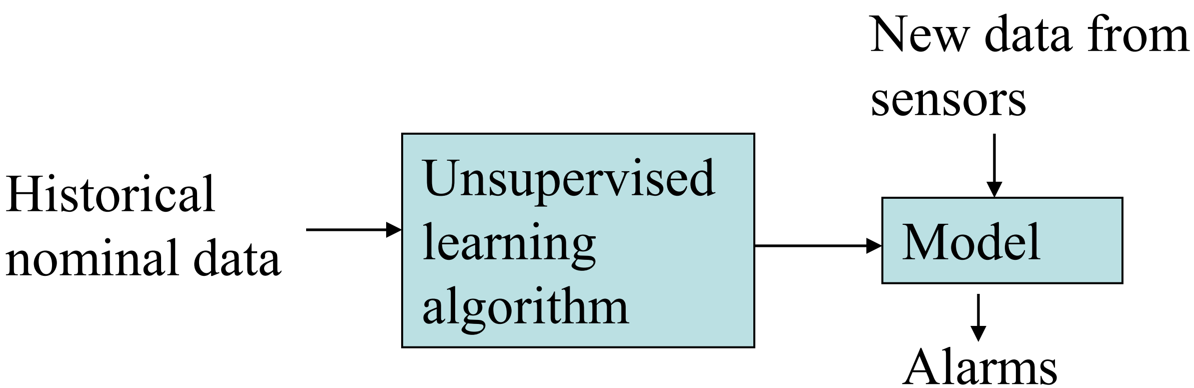


SHINE

- Rule-based expert system
- Uses a data-flow representation to execute rules efficiently
- Basis for four of the nine BEAM components
- Very fast: Over 300 million rules per second on current desktop computers
- Extremely small memory and storage footprint, suitable for embedded applications
- Applied to several mission ground ops including Voyager and EUVE
- Tested on flight hardware (X-33 AFE) and in flight (DFRC F/A-18)
- We used SHINE to provide the “wrappers” for TEAMS-RT
  - Mode and event identification
  - “pass/fail” test results

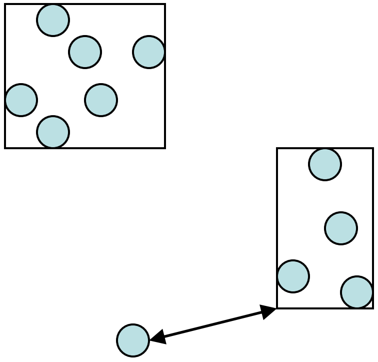
Unsupervised Anomaly Detection

- Unsupervised anomaly detections algorithms look for portions of the data that are different from the rest of the data (outliers).
- Unsupervised approach to fault detection uses only nominal training data, and learns a model of the nominal data. When new data doesn’t match the model, it signals an alarm.
- Can catch unknown faults
- Does fault detection only, not diagnosis
- Useful when few examples of faults are available
- Can detect interactions among hundreds of variables
- Ames’ IMS and Orca and JPL’s BEAM use this approach. (BEAM can also use a physics-based model and/or supervised learning)



IMS

- Data-driven unsupervised learning algorithm
- Inductive Monitoring System (IMS)
  - clusters the training data
  - uses distance to nearest cluster as anomaly measure
- Developed by Dave Iverson of ARC
- Is currently running on a console at JSC MCC to find anomalies in live ISS CMG data and has been certified as Class C software for that application.
- Also used to find anomalies in historical SSME data
- Runner-Up in the 2008 NASA Software of the Year Competition
- Generic C++ code



Data used for testing our software

- Before the Ares I-X data became available, we used historical Shuttle TVC and HSS data to train and test our software.
- We inserted simulated failures into the historical Shuttle data.
- The prototype ran on live Ares I-X data from the VAB and from the pad.

Simulated failure modes in Shuttle data

- FSM (Fuel Supply Module) pressure drop due to N_2H_4 (Hydrazine) leak
- Hydraulic pumping unit over-temperature failure
- Hydraulic fluid reservoir level drop due to hydraulic fluid leak
- Actuator stuck during actuator positioning test

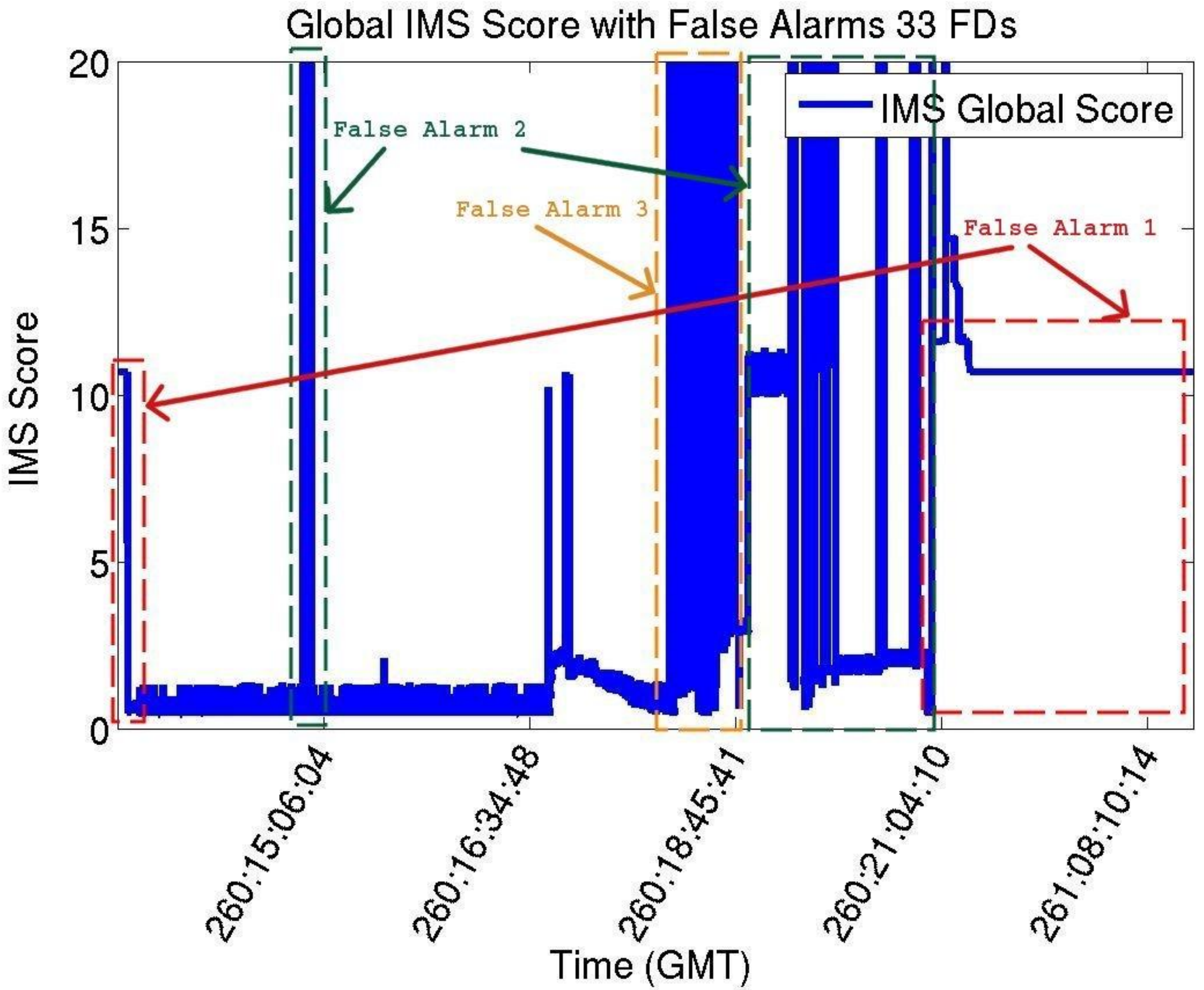
TEAMS/SHINE results on Shuttle data

- Tested the prototype on data from 7 Shuttle flights with simulated failures
- Testing revealed some bugs, which we fixed
  - Some bugs caused by incorrect assumptions about TVC testing procedures
- After fixing bugs, prototype ran on all 7 flights with all simulated failures correctly detected and no false alarms.

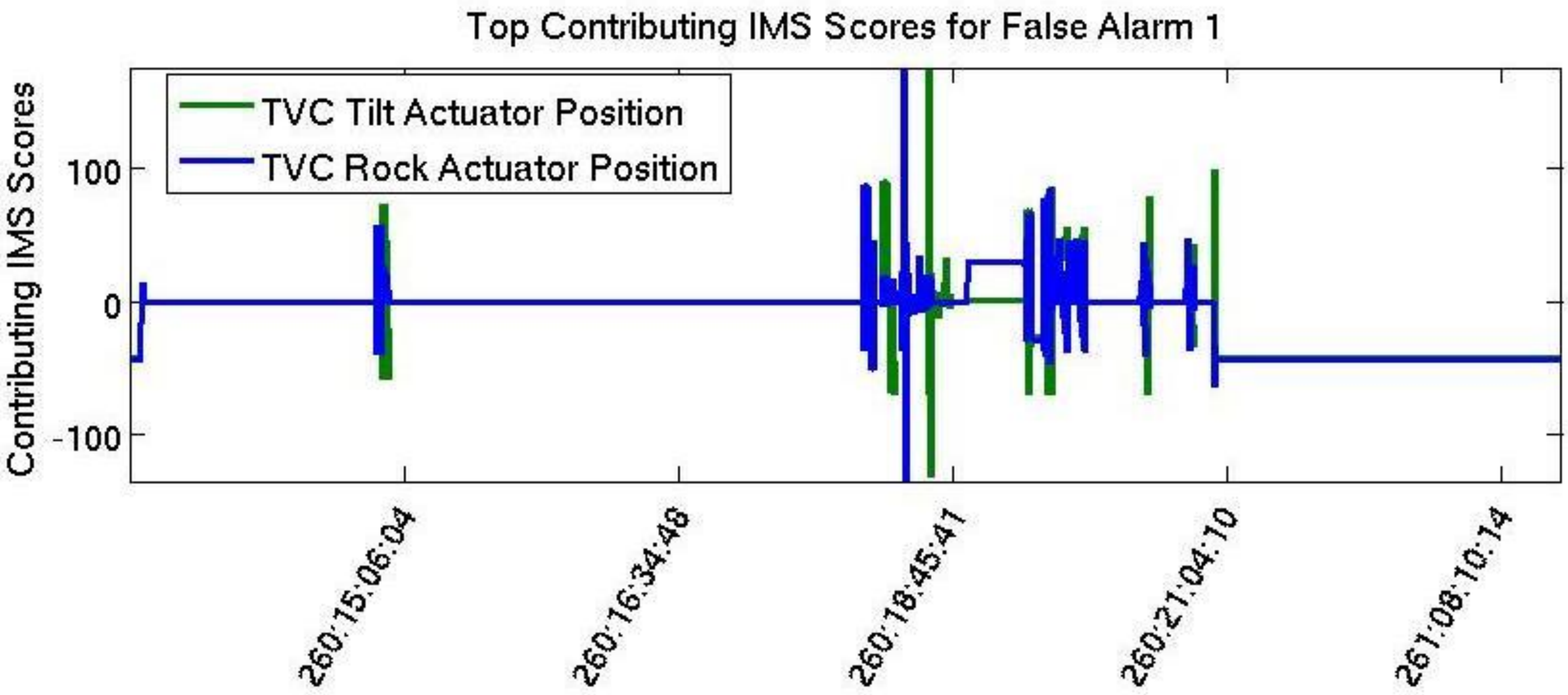
TEAMS/SHINE results on Ares I-X data

- First test on Ares I-X data after initial VAB power-up
  - Some false alarms caused by differences between Shuttle and Ares I-X TVC test procedures
  - SHINE rules fixed
- Shortly before launch, some false alarms caused by data dropouts
  - We had expected dropouts during ascent, but not before launch
  - After launch, we modified our code to detect data dropouts
  - Ran modified code on launch data with no false alarms
- Ares I-X had no failures in the systems we modeled.
  - Prototype had no missed detections and no correct detections.

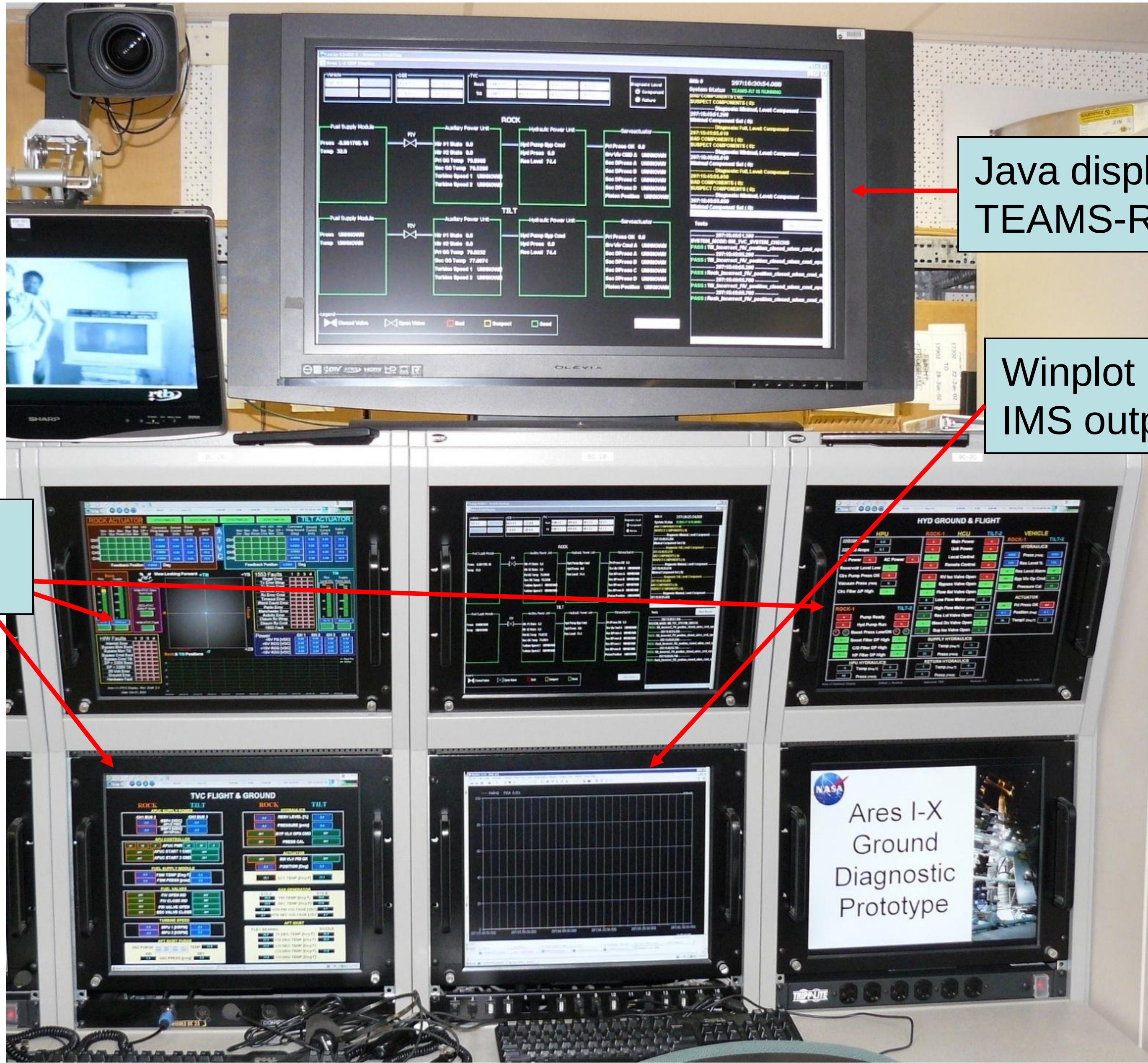
IMS results for Ares I-X VAB data



IMS Contributing scores for Ares I-X VAB False Alarm 1



GDP Console in Hangar AE

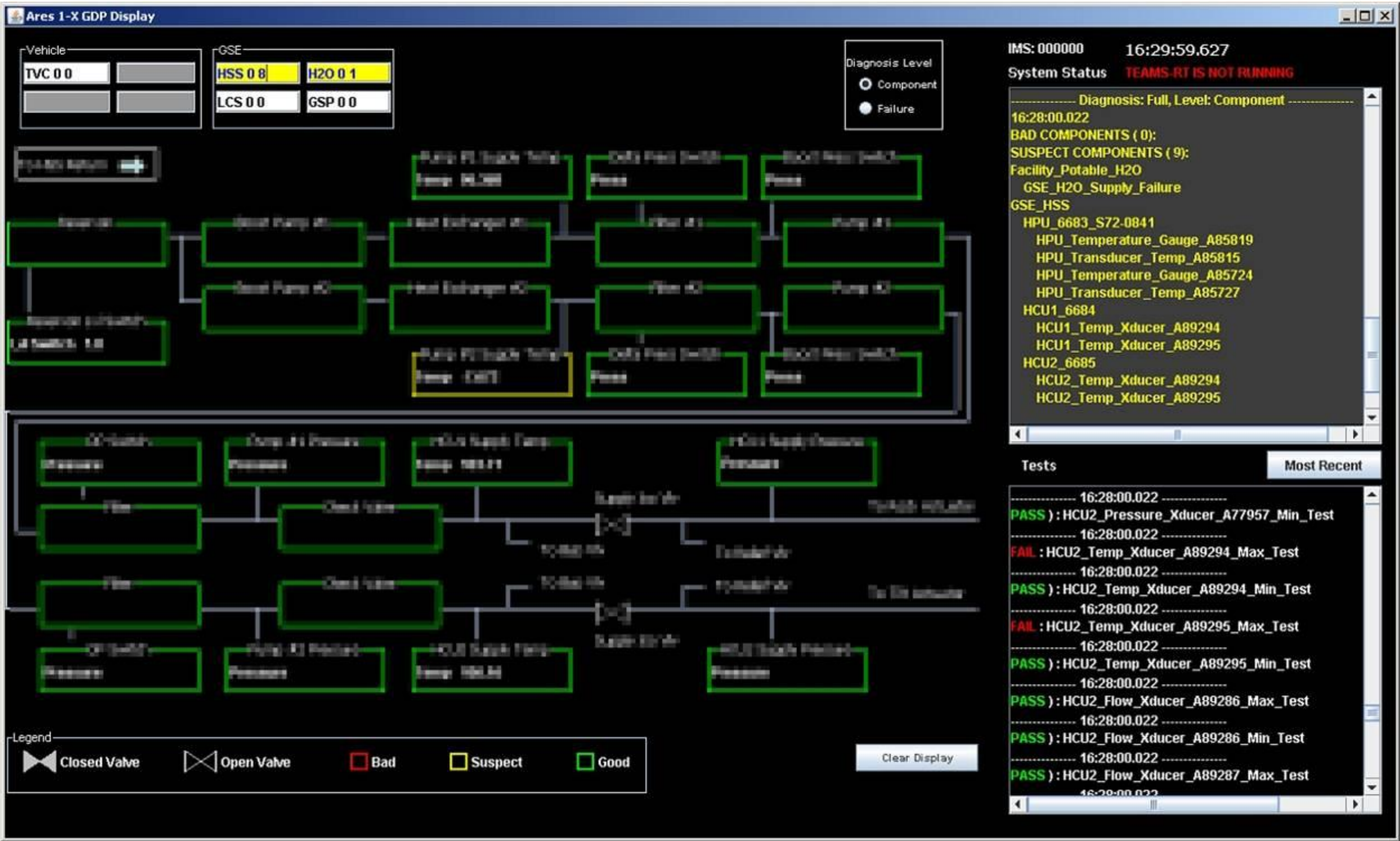


Java display of TEAMS-RT outputs

Winplot display of IMS outputs

Ares I-X Iris displays

GDP Screen Shot



Computational Performance

- Dell Precision M4400 laptop with an Intel Core 2 Quad Q9300 CPU running at 2.53 GHz and 4 GB of DRAM
- 655 components, 893 failure modes, 263 tests, 281 measurements

Process	CPU	DRAM
TEAMS (includes TEAMS-RT, the SHINE rules, the C test logic, and the data interface code)	8%	12 MB
IMS (including its data interface code)	1%	11 MB
Java display (including JVM)	1%	29 MB
Data playback software	18%	56 MB
Plotting tool	1%	12 MB
Windows XP Operating System	5%	410 MB
Total	34%	530 MB

Lesson Learned: Appropriate Roles for Model-Based and Data-Driven Tools

- Model-based tools should be used to detect failure modes that are well understood.
- Data-driven tools should be used to detect unknown failure modes.

Conclusions

- Automated pre-launch diagnostics can help increase safety, reduce cost, and reduce launch delays.
- The Ares I-X Ground Diagnostic Prototype helped to demonstrate and mature automated fault detection and diagnostic software that can be used in future missions.
- GDP demonstrated the feasibility of integrating 3 methods and of integrating the vehicle with the ground systems.
- IMS had some false alarms, as expected, since not all anomalies are failures.
- We believe that the number of false alarms in IMS will decrease over time as more data becomes available.
- We believe the TEAMS false alarms could have been avoided with better V&V.